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GE/EE/77-1

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(6) IMPLEMENTATION OF A METHOD TO DETECT
THE SINGLE VISUAL EVOKED RESPONSE.

(11) Jan 77

(9) Master's THESIS,

(12) 59 p.

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Capt   USAF

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IMPLEMENTATION OF A METHOD TO
DETECT THE SINGLE VISUAL EVOKED RESPONSE

Thesis

Presented to the Faculty of the School of Engineering

of the Air Force Institute of Technology

Air University

in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

by

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Graduate Electrical Engineering

January 1977

Preface

This report is the result of my attempt to implement a method of detecting the single visual evoked response (VER). The problem is analogous in many respects to the radar detection problem. That is, a small signal containing the useful information is buried in a higher amplitude noise background. There are, however, a considerable number of variables in evoked response detection not all of which are fully understood. The relationship of the signal (VER) and the noise (on-going electrical activity of the brain) is a prime example.

Most of the visual evoked response research to date has dealt with the averaged VER. This requires the presentation of a large number of stimuli and the computation of an averaged response. There are possible applications of the VER that require positive detection after a single stimulus presentation. It was toward this end that this project was undertaken.

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Abstract

The visually evoked response (VER) is one neural response
to an external event. (Although, with) ~~Through~~ computer averaging techniques
the evoked response to a particular stimulus is readily avail-
able, ~~However,~~ there are ~~some~~ anticipated applications which
require detection of the VER after a single stimulus presenta-
tion. The approach in this report

This report describes an attempt to detect the single
visual evoked response. The approach taken is based on the
similarity of the problem to that of radar detection in
which a known signal is buried in noise. Using ~~the~~ discrete
Fourier transform ~~(DFT)~~ and other digital signal processing
techniques, a filter matched to the VER template was computed
and implemented on a digital computer.

Computation of the matched filter required an estimate
of the noise power spectrum, where the noise in this case is
the on-going electrical activity of the brain. This was ac-
complished by averaging modified periodograms. Data from
both the vertex and occipital regions were filtered to deter-
mine if one region produced better results than the other.

The results indicate that the matched filter will detect
the single evoked response, However, the false alarm rate
is high. The filtered output for data from both regions indi-
cate there were several stimuli in a given time period when
few were actually presented. These results give rise to the
conclusion that some components of the on-going activity match
well with the filter. It is suggested that the effectiveness

of the matched filter approach may be improved by prefilter-
ing the sample data to remove the contaminating components.

IMPLEMENTATION OF A METHOD TO
DETECT THE SINGLE VISUAL EVOKED RESPONSE

I. Introduction

The visually evoked response (VER) is one neural response
to an external event. In practice, discrete visual stimuli
such as light flashes can be discerned in the electroenceph-
alogram (EEG), and these representations provide valuable in-
formation concerning the processing of the visual stimulus.
However, the neural event generated in response to this stim-
ulus is extremely small with respect to the on-going, spon-
taneous electrical activity of the brain as measured by the
EEG, creating a signal-to-noise ratio which is unfavorable.
The typical way to improve this ratio has been to average the
response to a great number of stimulus presentations, allowing
the average of the random activity to build slowly, while the
actual evoked response builds quickly. While satisfactory in
many applications, this technique precludes using the evoked
response in a number of other applications. In particular,
there are instances in which the VER is useful only if it can
be detected after one stimulus presentation.

Purpose

The purpose of this research was to implement a method of
detecting the visually evoked response after a single stimu-
lus presentation. The scope of this work is limited to the
signals and signal detection scheme used in the implementa-

tion. However, a brief discussion of the means of obtaining the experimental data is in order and will be presented in Chapter II.

Background

Approach. The approach taken was to consider signal detection methods known from information processing theory. The matched filter technique was selected since response detection, and not reproduction (fidelity) of the response was the primary objective.

A matched filter maximizes the ratio of the peak signal to rms noise and is used to detect the presence of the individual evoked response following a stimulus presentation. With the matched filter the output signal-to-noise ratio is a function solely of the energy in the signal (VER) and the spectral density of the on-going background activity which will be referred to as noise. It is the energy in the signal that provides its ultimate detectability in noise (Ref. 1:416).

The filter was constructed (e.g., simulated on a digital computer) from a template of the VER. When an individual evoked response to a single stimulus presentation closely matches the template the filter output is maximized. That is, the filter output is a pulse which indicates that the stimulus was perceived by the brain. In essence, the matched filter procedure is a cross-correlation between the expected waveform (or template) and the incoming data. When the two match well, the resulting cross-correlation is high.

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If a predetermined threshold is exceeded the decision is made that an evoked response has occurred.

Assumptions. The implementation of the approach outlined above required some basic assumptions to be made. First, it was assumed that the signal activity will be similar with each stimulus presentation. It was also assumed that the averaged VER is a valid representation of each individual evoked response. A further assumption was to assume that the background activity and evoked response are additive. And, finally, the noise activity and the VER were assumed to be uncorrelated. The validity of these assumptions will be discussed along with the results in Chapter IV.

Relationship of the EEG and VER. The EEG and VER are complex phenomena whose specific electrogeneses are unknown (Ref. 2:40). The background activity is approximately ten times as great as the evoked response to a single visual stimulus with both having amplitudes measured in microvolts.

The EEG is often considered to be a mixture of activity compartmentalized into various frequency ranges. Starting with the low frequency range there is the delta rhythm or activity which is usually described as less than 4 Hz. Delta rhythm does not usually appear in normal awake adults. Next, the theta activity appears in the frequency band of 4-7 Hz. This activity is usually of low voltage. The most often encountered activity is alpha, which occurs in the range of 8-13 Hz. This activity is usually large and quite prominent. Alpha or alpha-like activity appears to be the major contaminant of the VER. The two remaining rhythms are beta,

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usually described as low voltage, fast EEG in the range of
18-30 Hz, and gamma which occupies the frequency range of
35-50 Hz. This latter activity is seldom encountered or de-
scribed and has little general acceptance (Ref. 3:25-26).

The data acquisition procedure is discussed in Chapter
II. A complete discussion of the signal detection metho-
dology follows in Chapter III. Results are presented and
discussed in Chapter IV. An outline of the conclusions
drawn and recommendations for future work are offered in
Chapter V.

II. Data Acquisition

Data were obtained via a VER experiment designed by
Major Robert O'Donnell of the Aerospace Medical Research
Laboratory at Wright-Patterson Air Force Base, Ohio. The
experiment was designed to optimize the averaged evoked re-
sponse and thus increase the chances for successful detec-
tion. The experimental procedures and instrumentation are
described in great detail by a previous Air Force Institute
of Technology thesis (Ref. 4:8-33). In running a VER experi-
ment there are many variables to be considered which influ-
ence the VER. Perry and Childers present a detailed discus-
sion of these variables and their effect on experimental
results (Ref. 3:49-84).

In its basic form the VER experiment consists of the
following steps. Electrodes in contact with the scalp con-
duct the continuous electrical activity to an amplifier.
The amplified signal is then fed to a signal averaging com-
puter. If the signal were recorded prior to entering the
computer, it would be described as the EEG. In order to
obtain a VER, the computer triggers the light stimulus some
predetermined number of times and simultaneously averages
the scalp electrical activity evoked between stimuli. The
resulting average of the nonrandom activity is the VER. A
control or noise trial is obtained in exactly the same man-
ner, except the stimulus is occluded.

Data Description

For purposes of this research four channels of information were recorded. One channel consists of vertex data with a second channel containing the occipital information. The third and fourth channels contained timing and stimulus triggering data. All follow-on data processing was duplicated to determine which region produced the higher probability of evoked response detection.

The experiment consisted of two parts. During the first series the template was constructed. In the second part test data were recorded which would allow study of the background activity while at the same time providing sample data. This sample data would later be used to test the matched filter.

Template Construction. Eight averaged VER's were obtained for each channel. The stimulus rate used was one presentation every five seconds for eight periods of five minutes each. A black and white checkerboard pattern was used as the stimulus. The individual responses for each period were computer averaged to arrive at the eight averaged VER's mentioned previously. One template for each channel was then computed by taking the average of these eight. The resulting templates are shown in Figs. 1 and 2 respectively. Each template is approximately 20 microvolts peak-to-peak (maximum) and 500 milliseconds in duration.

Sample Data. The sample data were obtained by running three 10 minute sessions on the day after the templates were constructed. A random stimulus presentation rate was used
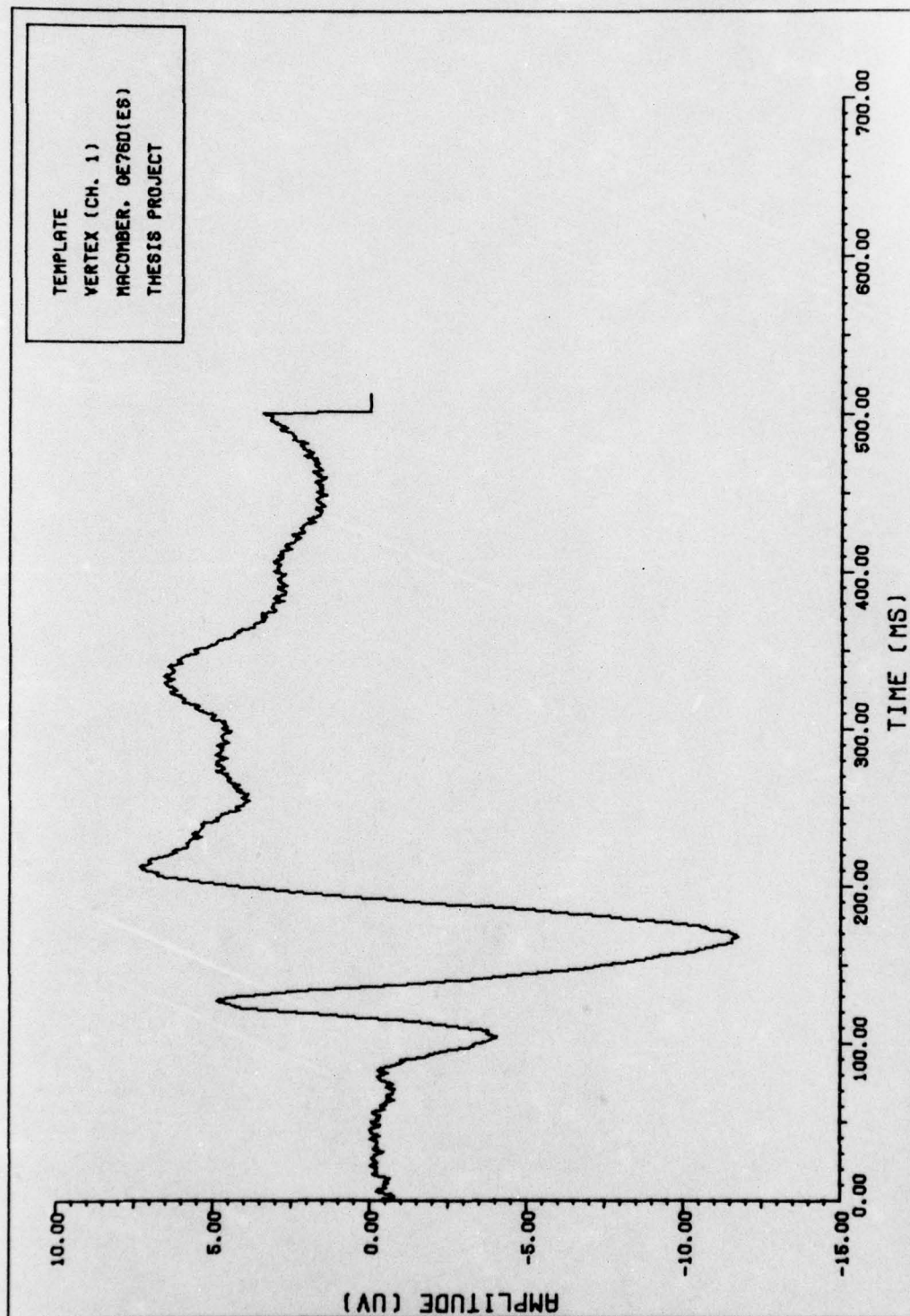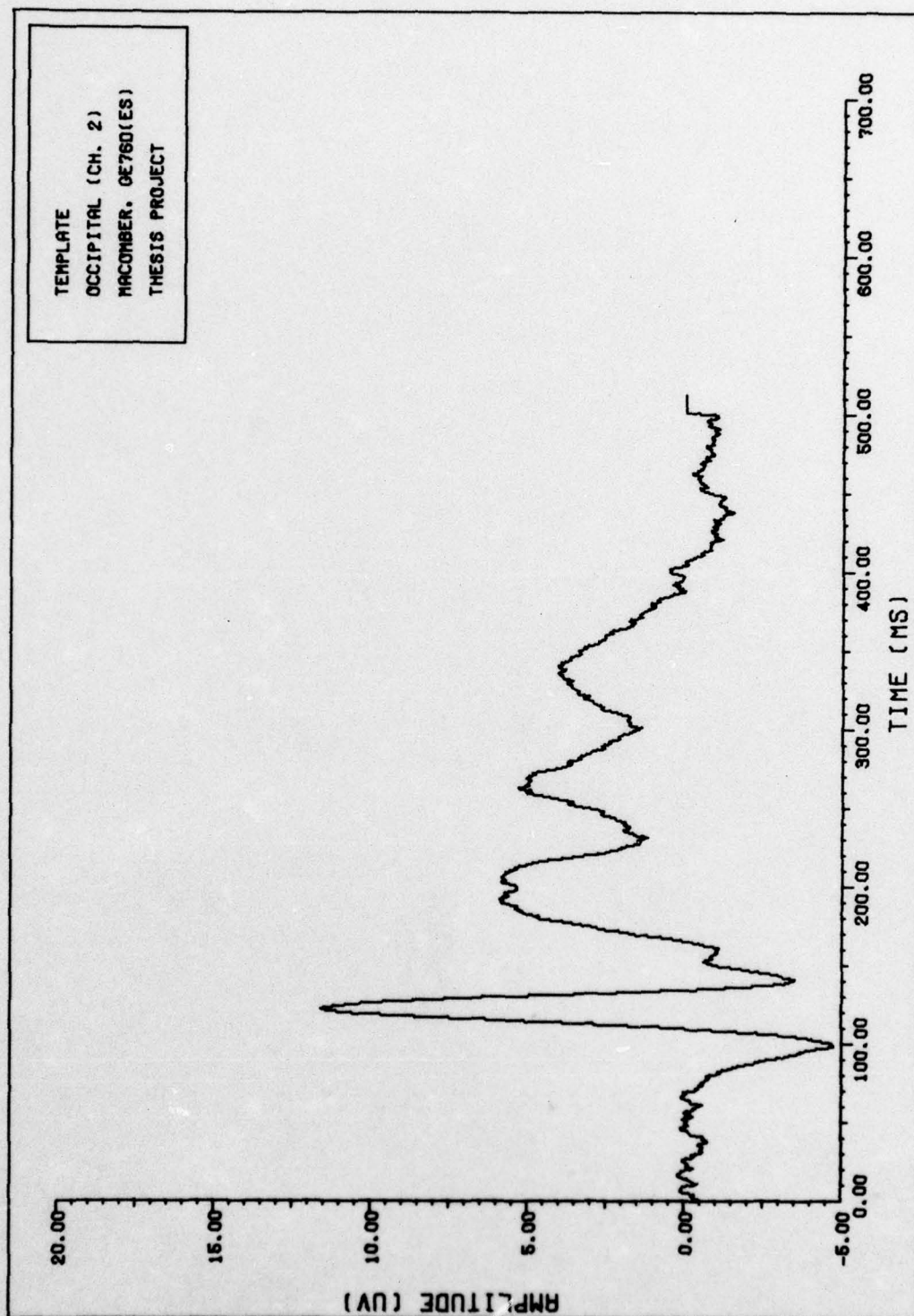
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FIGURE 1.   VERTEX TEMPLATE

FIGURE 2. OCCIPITAL TEMPLATE

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for each of these sessions. For the first run the rate was
an average of one stimulus every 60 seconds. Next, an aver-
age rate of one every 30 seconds was used, and for the final
session one every 10 seconds. Since the evoked response has
little effect on the background activity the combined 30
minutes of sample data were assumed to approximate raw EEG
for purposes of noise computations. Examples of vertex and
occipital data are shown in Figs. 3 and 4 respectively. The
time period for each sample is six seconds and the approxi-
mate peak-to-peak maximum amplitude is 100 microvolts.

Analog-to-Digital Conversion

All data were digitized on the hybrid computer facility
of the Computer Science Center at Wright-Patterson Air Force
Base, Ohio. Personnel of the Analog and Hybrid Branch devel-
oped programs to digitize the data, convert it to a 60-bit,
CDC 6600 compatible representation, and store it on magnetic
tapes. A sampling rate of 1000 per second was used which
far exceeds the minimum requirement to sample at twice the
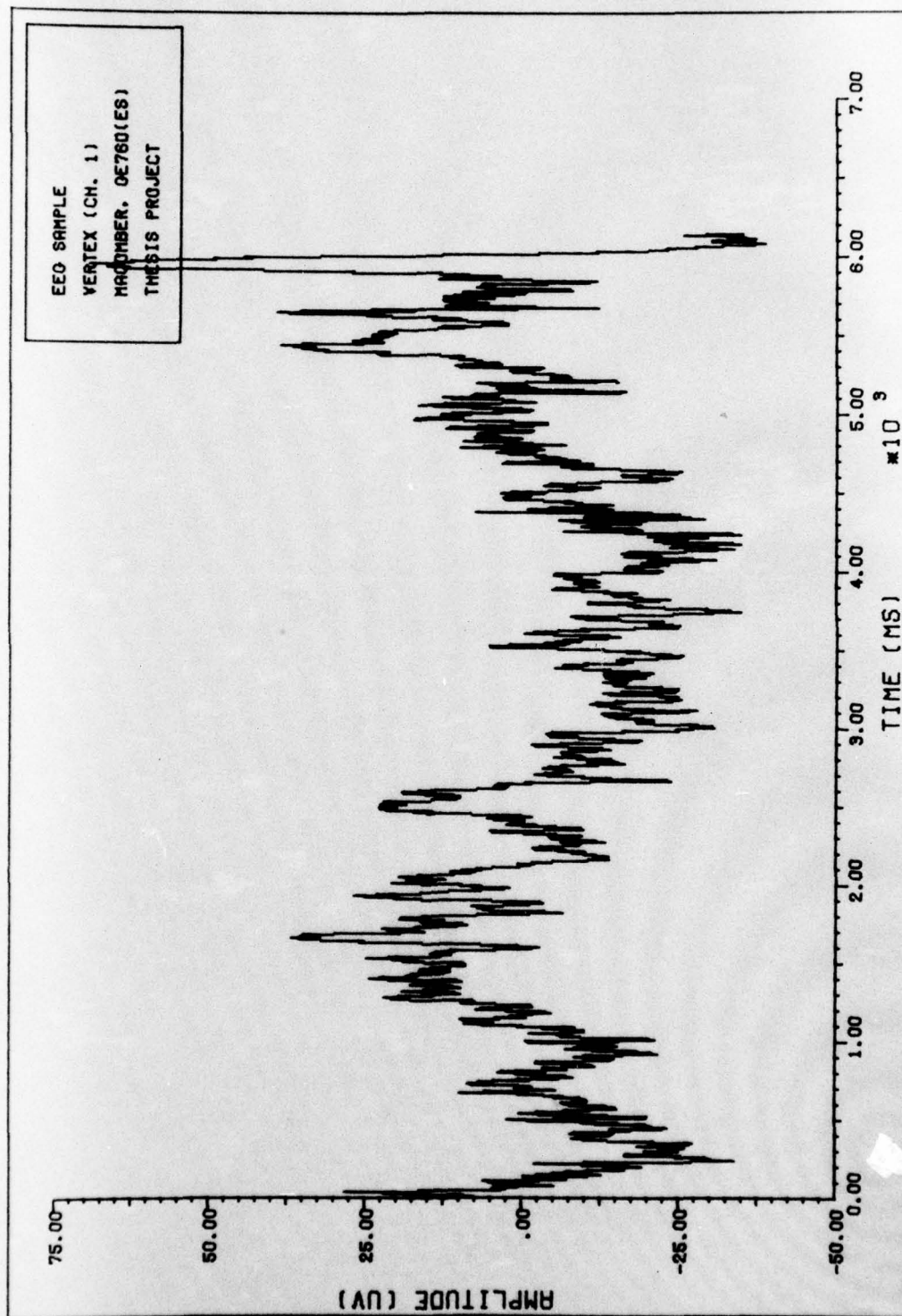highest signal frequency.

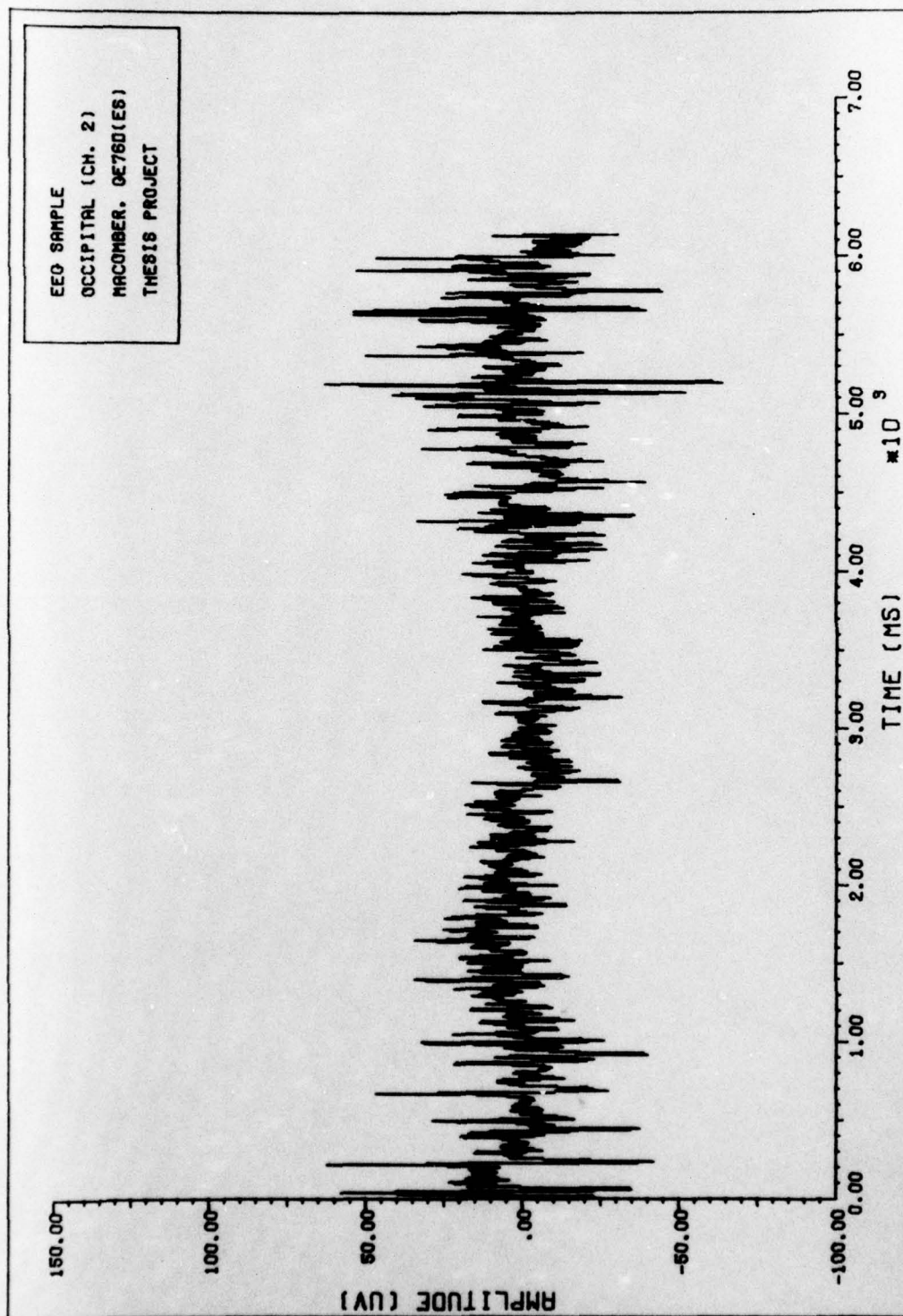FIGURE 3. VERTEX EEG DATA SAMPLE. 1-6 SEC.

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FIGURE 4.   OCCIPITAL EEG DATA SAMPLE. 1-6 SEC.

EEG SAMPLE
OCCIPITAL (CH. 2)
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III. Matched Filter Design and Implementation

The fundamental problem to solved is the detection of
a known signal that is buried in noise. Its solution calls
for a filter which will maximize the signal-to-noise ratio
at its output. Under the assumptions listed in Chapter I
matched filtering is the optimum method of implementing this
solution.

This chapter begins with an overview of the matched fil-
ter derivation. Following this is a discussion of the
matched filter simulation using the digital computer. In-
cluded in this discussion are a description of the discrete
Fourier transform (DFT) and the method used to determine the
noise power density spectrum. And, finally, the filtering
algorithm used to filter the sample data is presented.

Matched Filter Derivation

Considering the VER template as the signal $s(t)$, its
frequency spectrum $S(f)$ is given by the Fourier transform

$$S(f) \ = \ \int_{-\infty}^{\infty} s(t)e^{-j2\pi ft}dt \ . \tag{1}$$

The signal is applied with additive noise, $n(t)$ (the on-
going background activity), to the input of a linear filter
with transfer function $H(f)$. It is desired to determine the
characteristics of $H(f)$ that will give the greatest ratio of
peak signal to rms noise at the output when the input, $x(t)$,
is $s(t) + n(t)$. The linear aspects of the filter allow the

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signal and noise to be treated separately and the output results added.

If signal, $s(t)$, alone is applied to the filter, the output , $g(t)$, is given by

$$g(t) = \int_{-\infty}^{\infty} S(f)H(f)e^{j2\pi ft} \, df \ . \tag{2}$$

The magnitude of $g(t)$ will be maximum at some time $t = t_o$, or

$$\left| g(t_o) \right| = \left| \int_{-\infty}^{\infty} S(f)H(f)e^{j2\pi ft_o} \, df \right| \geq g(t) \ . \tag{3}$$

If the input noise power density is considered to be $B(f)$ watts/Hz, the mean square noise power at the output of the filter, N_o, is seen to be

$$N_o = \int_{-\infty}^{\infty} B(f) \left| H(f) \right|^2 df \tag{4}$$

where,

$$B(f) = \left| A(f) \right|^2 . \tag{5}$$

The ratio to be maximized by the proper selection of $H(f)$ is the peak signal to rms output noise, $\left| g(t_o) \right| / \sqrt{N_o}$. This is accomplished by squaring, dividing by the energy in the input signal, E, and applying Schwartz's inequality. The steps required are shown below.

$$\frac{|g(t_o)|^2}{EN_o} = \frac{\left| \int_{-\infty}^{\infty} \frac{A(f)}{A(f)} S(f)H(f)e^{j2\pi ft_o} \, df \right|^2}{\int_{-\infty}^{\infty} B(f) |H(f)|^2 \, df \int_{-\infty}^{\infty} |S(f)|^2 \, df} \tag{6}$$

$$= \frac{\left| \int_{-\infty}^{\infty} \frac{S(f)}{A(f)} H(f)A(f)e^{j2\pi ft_o} \, df \right|^2}{\int_{-\infty}^{\infty} B(f) |H(f)|^2 \, df \int_{-\infty}^{\infty} |S(f)|^2 \, df} \tag{7}$$

$$\leq \frac{\int_{-\infty}^{\infty} \left| \frac{S(f)}{A(f)} \right|^2 \, df \int_{-\infty}^{\infty} |H(f)A(f)e^{j2\pi ft_o}|^2 \, df}{\int_{-\infty}^{\infty} B(f) |H(f)|^2 \, df \int_{-\infty}^{\infty} |S(f)|^2 \, df} \tag{8}$$

The ratio can therefore be maximized by letting

$$H(f)A(f) = \frac{S^*(f)}{A^*(f)} \quad , \tag{9}$$

or,

$$H(f) = \frac{S^*(f)e^{-j2\pi ft_o}}{A(f)A^*(f)} \tag{10}$$

$$= \frac{S^*(f)e^{-j2\pi ft_o}}{B(f)} \quad . \tag{11}$$

The filter may have an attenuation or gain, K, that is not a function of frequency. Thus, for a non-white noise power

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density spectrum, the transfer function of the matched filter is,

$$H(f) = \frac{KS^*(f)e^{-j2\pi f t_o}}{B(f)}.$$ (12)

Equation (12) demonstrates that the optimum filter weights most heavily those spectral components of the input signal which greatly exceed the noise spectral density and de-emphasizes the spectral regions in which the noise spectral density is much larger than the signal spectrum (Ref. 5:146).

Matched Filter Simulation

The output of the analog-to-digital process described in Chapter I is a discrete time signal represented by a digital sequence $x(n)$. For this sequence it is possible to utilize an alternative Fourier representation referred to as the discrete Fourier transform (DFT). The DFT is a Fourier representation of a finite-length sequence which is itself a sequence rather than a continuous function. The DFT is essential for the computer implementation of a variety of digital signal processing problems. Computation time for the DFT has been reduced significantly by using fast Fourier transform (FFT) algorithms such as the one used in this study (Ref. 6:331). A detailed discussion of the DFT and derivation of computer algorithms for the FFT is presented in Reference (6).

The discrete Fourier transform of a sampled continuous

time function $f(t)$ is

$$F(kv) = \sum_{n=0}^{N-1} f(nT)e^{-jvTnk} \tag{13}$$

where,

$f(nT)$ are samples of $f(t)$, $0 \leq n \leq N-1$
T is the sampling interval
$F(kv)$ are samples of $F(f)$, $0 \leq k \leq N-1$
$v = 2\pi/NT$, and N = number of samples of $f(t)$.

Its inverse discrete Fourier transform (IDFT) is given by

$$f(nT) = \frac{1}{N} \sum_{k=0}^{N-1} F(kv)e^{jvTnk} . \tag{14}$$

Since the data were sampled at a rate greater than twice the highest frequency of $F(kv)$, the discrete-time Fourier transform of $f(nT)$ is equivalent to samples, equally spaced in frequency, of the Fourier transform of the sequence $f(t)$.

The discrete matched filter transform can therefore be written as

$$H(w) = \frac{KS^*(w)}{B(w)} \tag{15}$$

where $B(w)$ is the power density spectrum of the background activity. This is the discrete form of Eq. (12) with the exponential term dropped. The exponential serves to specify the time t_o where the peak output will occur. However, the delay inherent in the filter can be observed in the

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convolution of each template with its corresponding matched filter. For both cases $t_o = 512$ milliseconds as can be seen in Figs. 5 and 6.

The problem at this point, then, is to compute the DFT of the filter. In order to do this the background power density spectrum must first be derermined.

Noise Power Spectrum Estimation. The background activity is of indefinite duration and not periodic. Consequently, the discrete time signal which represents this activity can be modeled best in terms of an infinite-duration infinite-energy signal. Many of the properties of this type of signal can be summarized in terms of a finite-energy sequence called the autocovariance sequence, for which the Fourier transform exist. As will be developed below, the determination of the autocovariance sequence and its Fourier transform leads to a useful interpretation in terms of the frequency distribution of the power in the signal. For an exact signal the power density spectrum, $P(w)$, is defined as the Fourier transform of its autocovariance sequence.

The fundamental concept in the mathematical representation of infinite-energy signals is that of a random process. In the discussion that follows, it is assumed that the reader is familiar with fundamental concepts of probability and random processes.

The procedure used in determining a useful estimate of the noise power spectrum is basically the Welch method (Ref. 6:553-554). Implementation of this method calls for averaging
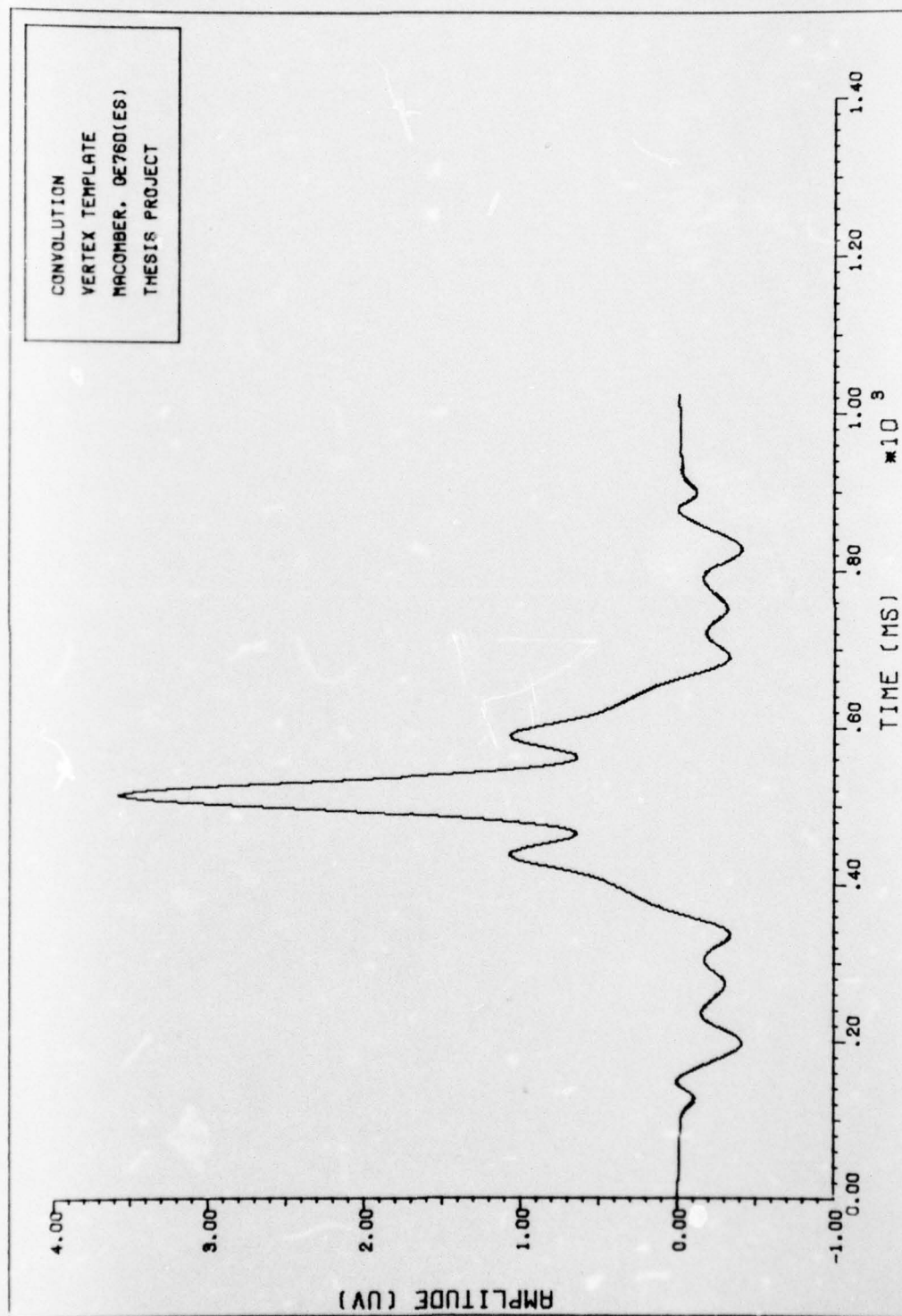
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FIGURE 5.   CONVOLUTION-FILTER & VERTEX TEMPLATE

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CONVOLUTION
OCCIPITAL TEMPLATE
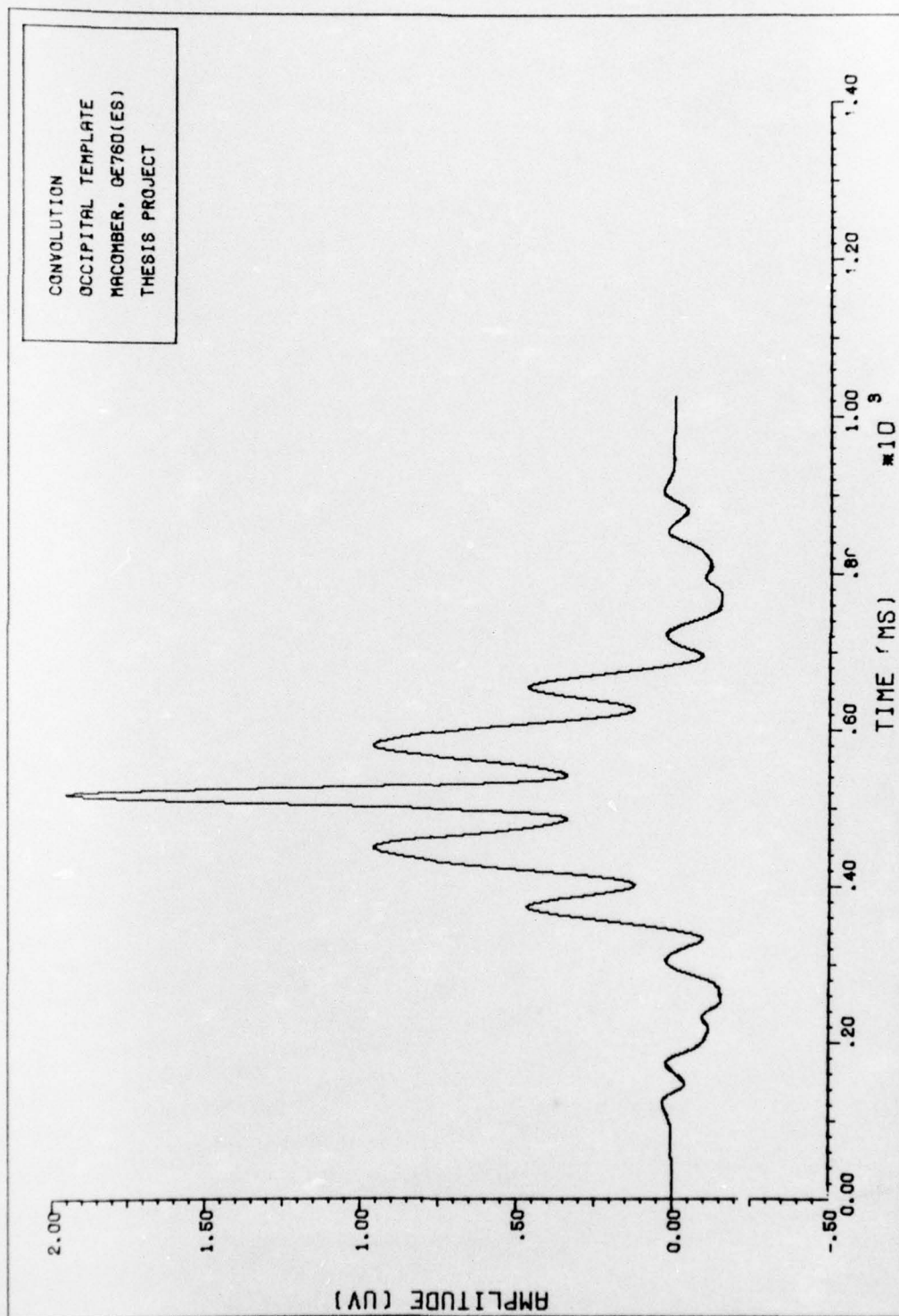MACOMBER. OE76D(ES)
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FIGURE 6.   CONVOLUTION-FILTER & OCCIPITAL TEMPLATE

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modified periodograms. Periodograms are themselves estimates
of the spectrum of a finite sequence. The usefulness of the
noise power spectrum so determined requires that it converge
to some meaningful result as the measurement interval in-
creases. A simple and useful way of defining convergence is
by requiring that the variance of the estimate approach zero
as the measurement interval increases (Ref. 7:399).

As an estimate of the power density spectrum consider the
Fourier transform of the biased autocovariance estimate c(m),
e.g.,

$$I_N(w) = \sum_{m=-(N-1)}^{N-1} c(m)e^{-jwn} . \tag{16}$$

Since the Fourier transform of the real finite-length
sequence x(n), $0 \leq n \leq N-1$, is

$$X(e^{jw}) = \sum_{n=0}^{N-1} x(n)e^{-jwn} \tag{17}$$

and it can be shown that

$$I_N(w) = \frac{1}{N} \left| X(e^{jw}) \right|^2 . \tag{18}$$

The spectrum estimate $I_N(w)$ is called the periodogram (Ref.
6:542). However, the variance of $I_N(w)$ does not approach
zero as N approaches infinity.

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$$\text{var} \left[I_N(w) \right] = \text{cov} \left[I_N(w), I_N(w) \right]$$

$$= P^2(w) \left[1 + \left[\frac{\sin(wN)}{\sin(w)} \right]^2 \right] \qquad (19)$$

Thus, the periodogram is not a consistent estimate.

A standard approach to reducing the variance of estimates is to average over a number of independent estimates. The application of this approach to spectrum estimation is often attributed to Bartlett (Ref. 6:548). Therefore, the data sequence x(n), representing the background activity, is divided into K segments of M samples each so that N=KM; e.g., forming the segments

$$x^{(i)}(n) = x(n+im-m), \ 0 \le n \le m-1, \ 1 \le i \le K . \quad (20)$$

Next, the K periodograms are computed from Eq. (21).

$$I_M^{(i)}(w) = \frac{1}{M} \left| \sum_{n=0}^{M-1} x^{(i)}(n) e^{-jwn} \right|^2, \ 1 \le i \le K \qquad (21)$$

The spectrum estimate is then defined as,

$$B(w) = \frac{1}{K} \sum_{i=1}^{K} I_M^{(i)}(w) . \qquad (22)$$

To determine if this is a useful estimate consider its variance as described in Eq. (23).

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$$\text{var}\left[B(w)\right] = \frac{1}{K}\,\text{var}\left[I_M(w)\right]$$

$$\approx \frac{1}{K}\,P^2(w)\left[1 + \left[\frac{\sin(wM)}{M\sin(w)}\right]^2\right] \tag{23}$$

It is clear that the variance of $B(w)$ is inversely propor-
tional to the number of periodograms averaged, and as K gets
large, the variance approaches zero. Therefore, the Bartlett
estimate is a consistent estimate.

The Welch method is a modification of the Bartlett pro-
cedure. It is particularly well suited for direct computa-
tion of the power spectrum estimate using the FFT. In this
procedure the data record is again sectioned into $K = N/M$ seg-
ments of M samples each as defined in Eq. (20). However, the
periodograms are modified by applying the triangular window
sequence, $w(n)$, directly to the data segments before computa-
tion of the periodogram. Thus, the K modified periodograms
are defined by

$$J_M^{(i)}(w) = \frac{1}{MU}\left|\sum_{n=0}^{M-1}x^{(i)}(n)w(n)e^{-jwn}\right|^2$$

$$i = 1,2,\ldots\ldots,K \tag{24}$$

where,

$$w(n) = \begin{cases} \dfrac{2n}{N-1}, & 0 \le n \le \dfrac{N-1}{2} \\[2ex] 2 - \dfrac{2n}{N-1}, & \dfrac{N-1}{2} \le n \le N-1 \end{cases}$$

and,

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2(n) \ .$$ (25)

The spectrum estimate is then defined as,

$$B(w) = \frac{1}{K} \sum_{i=1}^{K} J_M^{(i)}(w) \ .$$ (26)

Welch (Ref. 8) shows that if the segments of $x(n)$ are non-overlapping, such as in the present case, then

$$\text{var} \left[B(w) \right] \approx \frac{1}{K} P^2(w) \ .$$ (27)

This is the same as for the Bartlett method and is therefore a consistent estimate.

As described above, then, a consistent estimate of the noise power spectrum was computed by averaging modified periodograms. The sample data were divided into 3510 segments of 512 samples each. Each segment was multiplied by the 512 point window sequence and then a 512 point FFT algorithm was computed. The magnitude of the FFT for each segment was squared and the power spectrum $P(w)$ was determined by taking the average of these squares. Figures 7 and 8 show the spectrum for the vertex and occipital channels respectively. The magnitude shown is in $\log_{10}$ format.

Filter Response. The matched filter response was computed from Eq. (15) by first computing $H(w)$. Dividing the
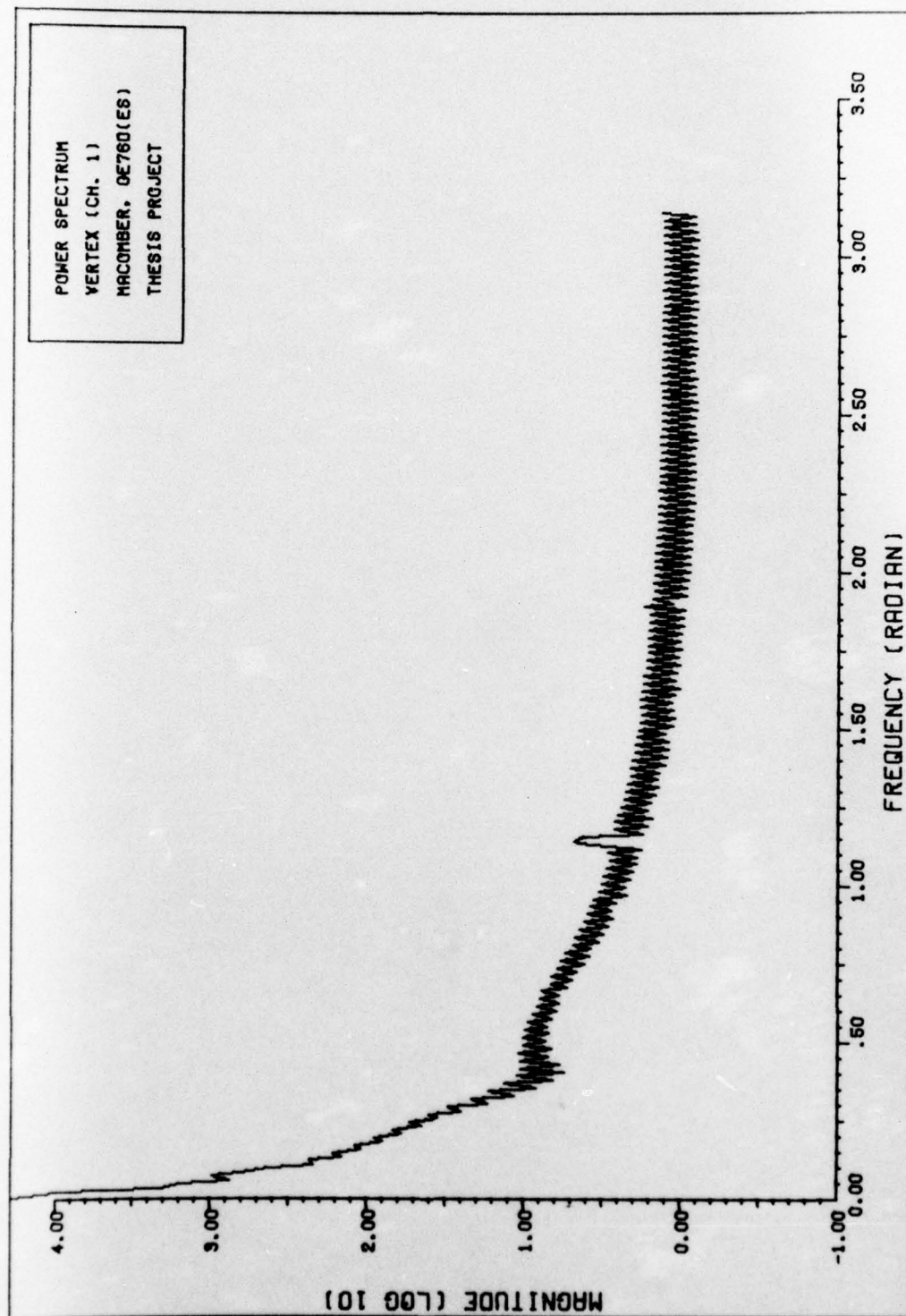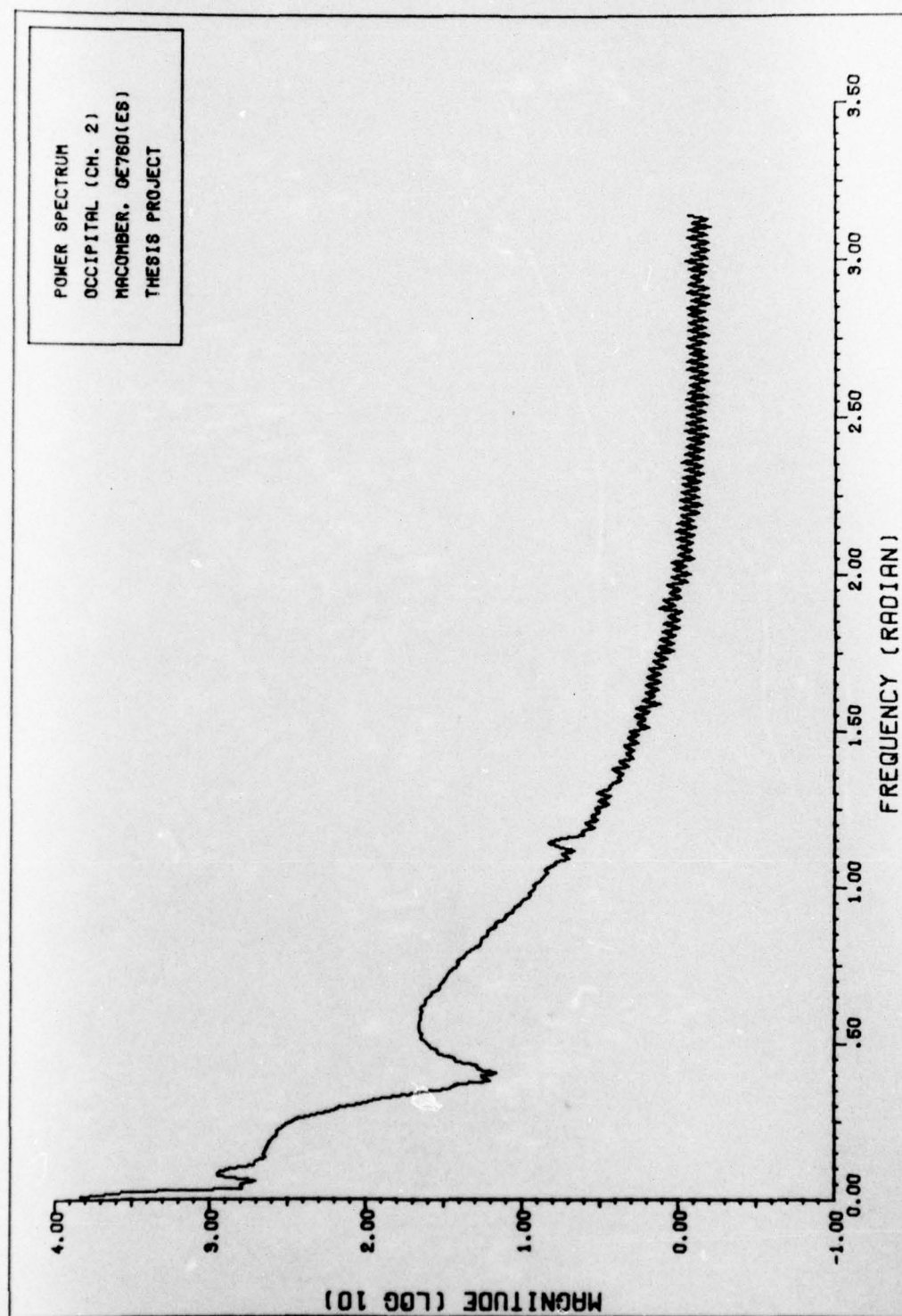
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FIGURE 7.   VERTEX NOISE POWER SPECTRUM

FIGURE 8. OCCIPITAL NOISE POWER SPECTRUM

complex conjugate of S(w) by B(w) yields H(w). The constant
K was arbitrarily set equal to one. Thus, the filter re-
sponse, h(n), is computed by finding the IDFT of H(w).

The first computation of h(n) did not produce the desired
results. Upon inspection of Figs. 7 and 8, the higher fre-
quency components are seen to be over emphasized. To correct
this condition the power spectrum for both channels were
modified. The curves were first mathematically smoothed.
Then, to reduce the peak magnitudes the eighth root of the
power spectrum was computed. The results of this procedure
are shown in Figs. 9 and 10.

The matched filter response for each channel was then
recomputed. As shown in Figs. 11 and 12, the resulting re-
sponse curves very closely approximate the template signals
running backwards in time.

Filter Implementation

In the general case the filtered output, y(n), is com-
puted by performing a linear convolution of the input signal
and filter response, e.g.,

$$y(n) = \sum_{n=0}^{N-1} x(m)h(n-m) \tag{28}$$
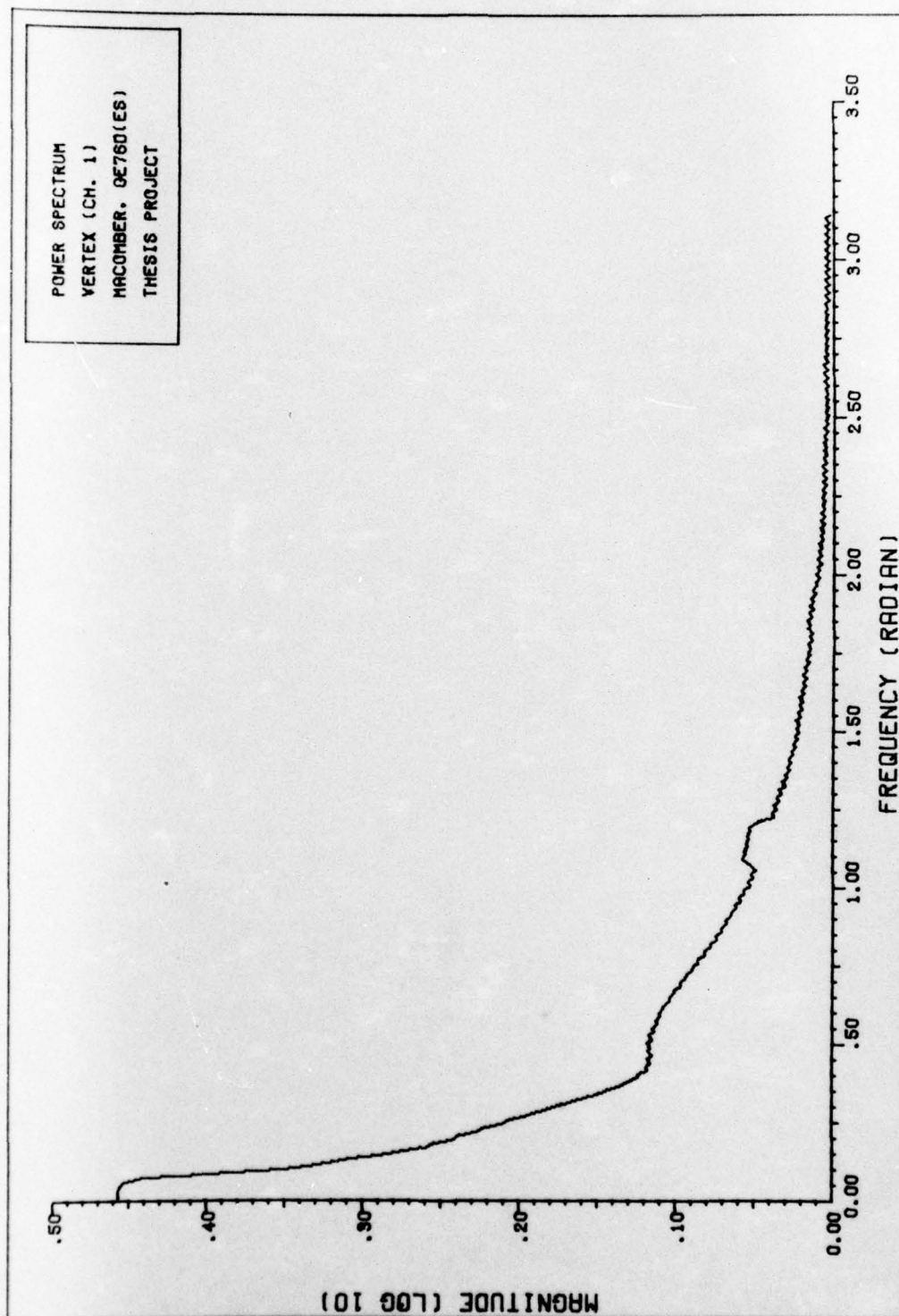
where,

x(n) is the input signal
h(n) is the filter response.

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FIGURE 9.   MODIFIED VERTEX NOISE POWER SPECTRUM
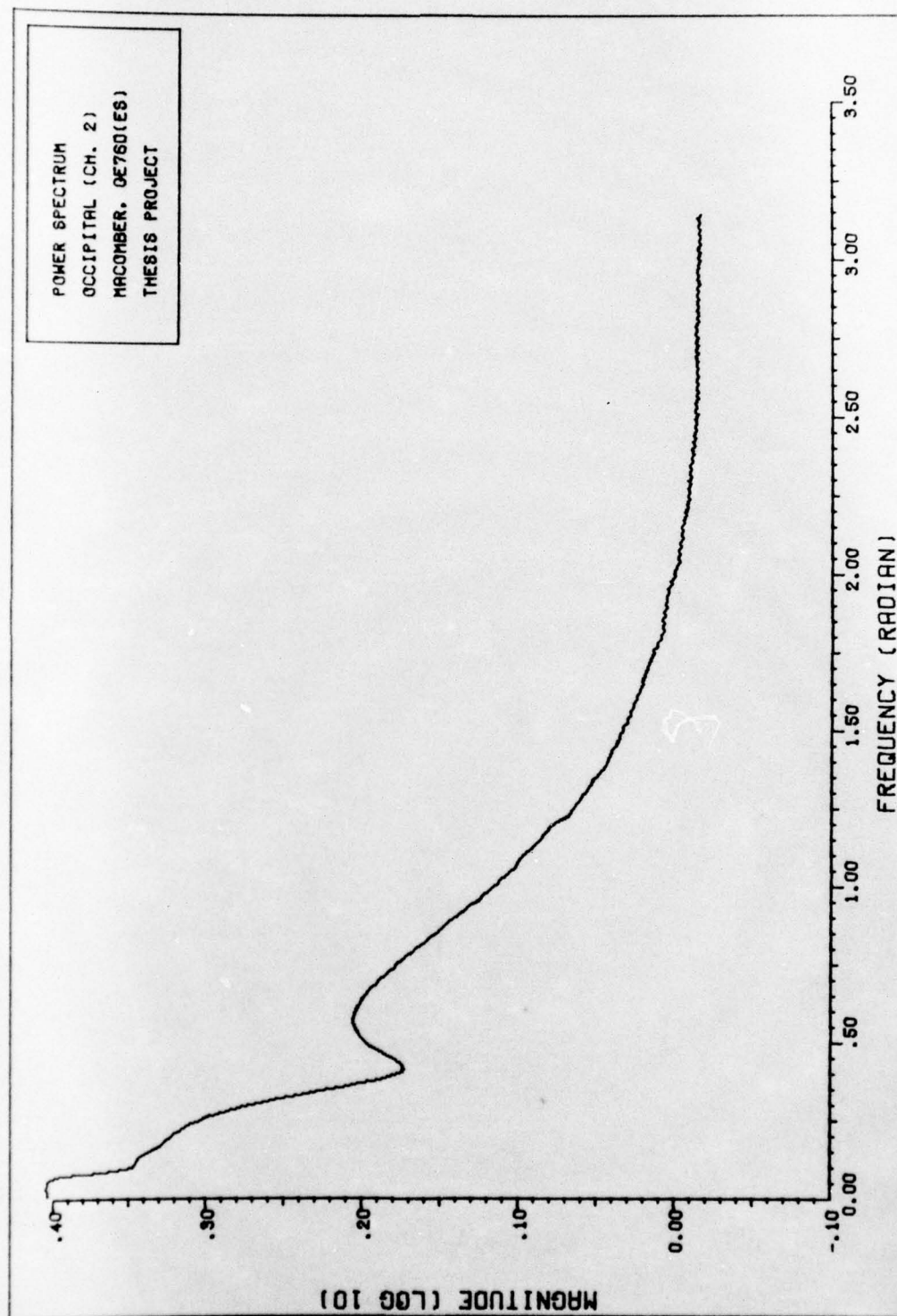
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FIGURE 10. MODIFIED OCCIPITAL NOISE POWER SPECTRUM

FILTER RESPONSE
VERTEX (CH. 1)
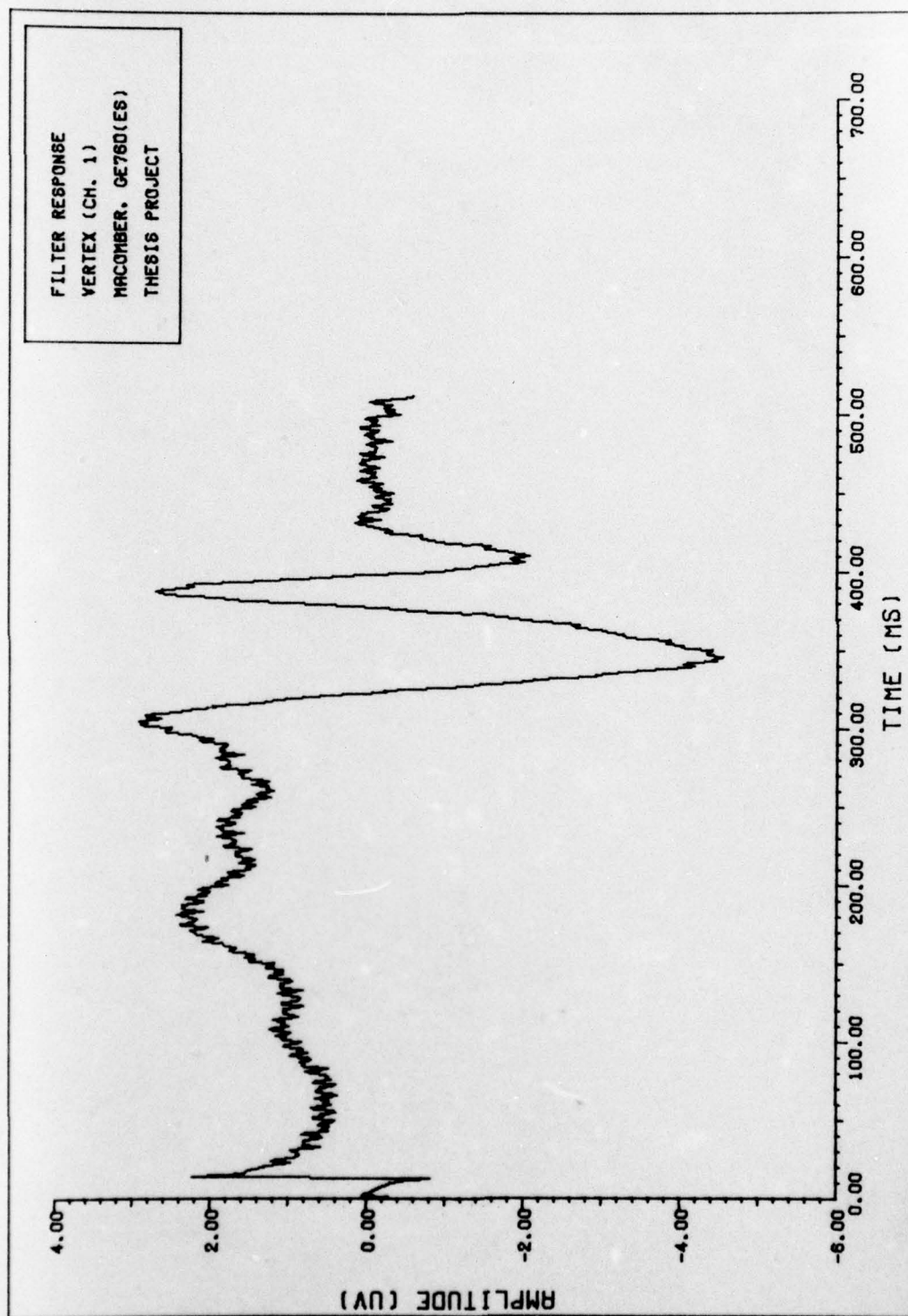MACOMBER. GE780(ES)
THESIS PROJECT
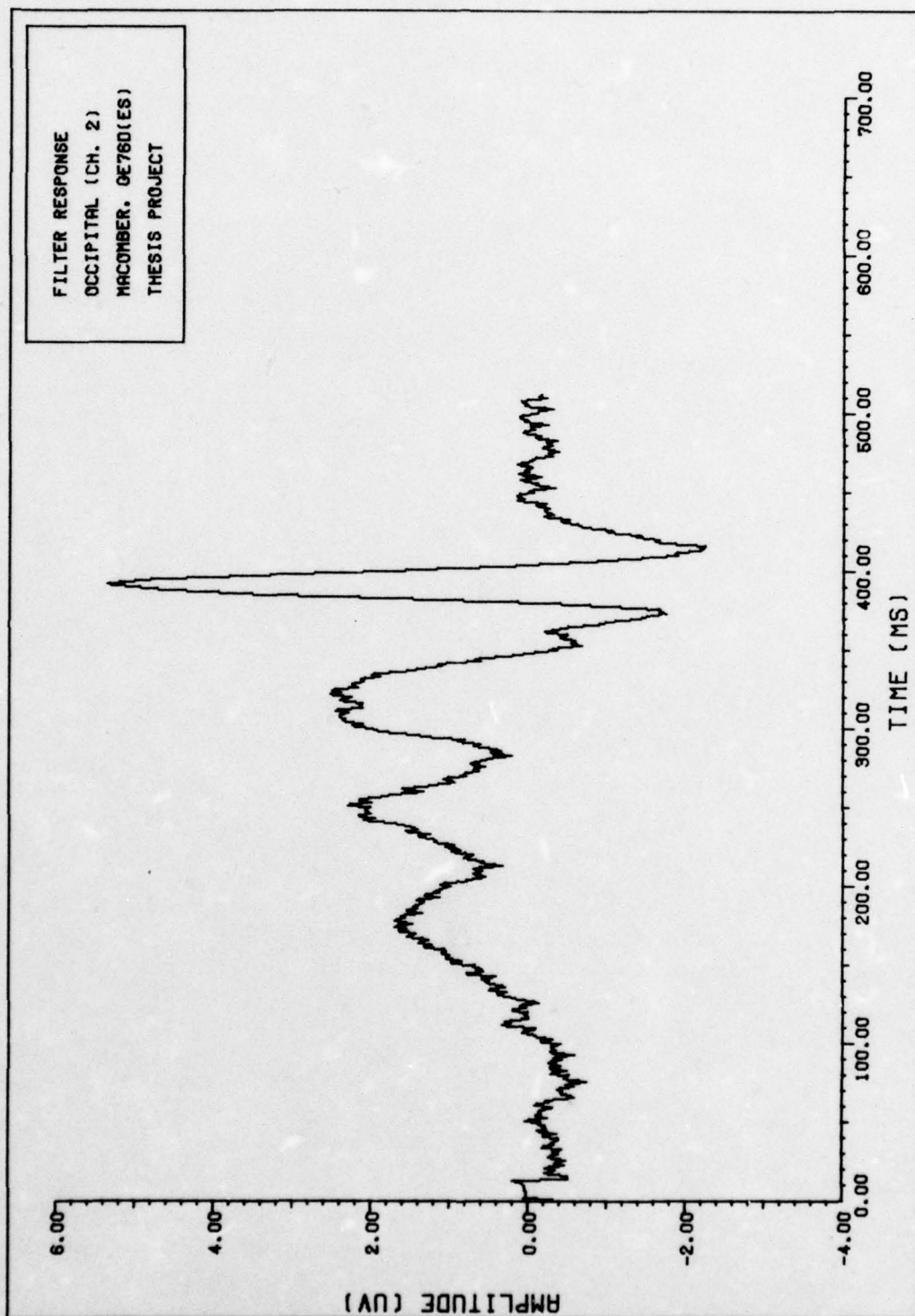
FIGURE 11.   VERTEX MATCHED FILTER RESPONSE

FIGURE 12. OCCIPITAL MATCHED FILTER RESPONSE

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If both $x(n)$ and $h(n)$ are N-point sequences the output sequence will have at most 2N-1 nonzero points.

For the problem at hand the input sequence is the on-going EEG containing randomly occurring VER signals. This sequence has an indefinite length and therefore must be segmented. The segment size selected was 512 points which is equal in length to the filter response sequence.

The discrete Fourier transform was utilized to effect the required linear convolution by performing a circular convolution between each input data segment and the filter response. A circular convolution is implemented by computing the DFT's of the two sequences, multiplying, and computing the IDFT of the product. To effect the linear convolution, however, there are some additional steps involved.

Prior to computing the DFT's the sequences must be zero filled to at least 2N-1 points. In this case each sequence was made 1024 points in length and the DFT's were then computed on this basis. To construct the filtered output for the entire input sequence the results for the individual filtered segments must be added in a particular manner.

The procedure used to construct the filtered output from filtered segments is referred to as the overlap-add method (Ref. 6:112-113). Each filtered segment of length 1024 points will overlap the previous segment by 512 points. Thus, each filtered segment is overlapped with and added to the previous segment to construct the filtered output. The program used to implement this procedure is included in Appendix A.

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Computer memory space requirements were high. To filter
30 seconds of data required approximately 200,000 octal words
and consequently this was the maximum amount of data filtered
per run. Results of the filter implementation are presented
in the following chapter.

IV. Results and Discussion

Using the computed filter response and the overlap-add
filtering scheme described in Chapter III, 30 second segments
of sample data were filtered for both the vertex and occipital
channels. The filtered output should show a positive peak
whenever a stimulus was perceived by the subject. This peak
should be well defined and have greater amplitude than the
output where no stimulus occurred.

The sample data were arranged in three 10 minute files
according to the stimulus rate used. File one is the one per
60 seconds rate; file two contains one stimulus per 30 seconds;
and file three contains the one per 10 seconds rate.

Data from each file were filtered producing similar results
in all cases. Therefore, the discussion that follows will be
limited to the results of filtering the first 90 seconds from
file one for both channels. Because the stimulus presenta-
tion rate is an average rate there are six stimuli occurring
in these 90 seconds. These occurred at 0,15,30,45,60, and
76.5 seconds into the experiment. To simplify the discussion
these will henceforth be referred to as stimulus A, B, C, D,
E, and F respectively.

As will become obvious upon examination of the filtered
output data, a decision as to whether or not a given evoked
response was detected is somewhat arbitrary. The criteria
for judging a positive detection was based primarily upon
the appearance of a sharp peak .5 to 1.0 seconds after the
stimulus was presented. First to be discussed is the vertex

data results followed by the results for the occipital data.

Results for Vertex Data

The vertex filter output is shown in Figs. 13A, B, and C. Clearly, the desired pattern is not in evidence. There are some peaks which are distinct and of greater amplitude than a majority of the remaining output. However, these do not coincide with the presentation of stimuli. Closer examination of the smaller peaks reveal concurrence (within .5 to 1.0 seconds afterward) with B, C, D, E, and F. The amplitude of these peaks ranges from 2.4 to 5.0 microvolts. Although the match between the filter and some of these single VER's is relatively poor they do indicate a positive detection rate of 83.3 %. This is speculative to be sure. It is apparent that the on-going background activity contains other components that match well with the matched filter. For instance, the high amplitude peaks appearing at approximately 39 and 80 seconds coincide with alpha or alpha-like rhythm in the background activity.

Results for Occipital Data

The occipital filter output is shown in Figs. 14A, B, and C. As with the vertex filter the desired output was not achieved. Again there are some peaks which coincide with the presentation of stimuli. Specifically, these appear for A, B, C, D, and F with amplitudes ranging from 1.75 to 5.0 microvolts. This would also indicate a positive detection rate of 83.3 %. It should be noted that high amplitude peaks occur at
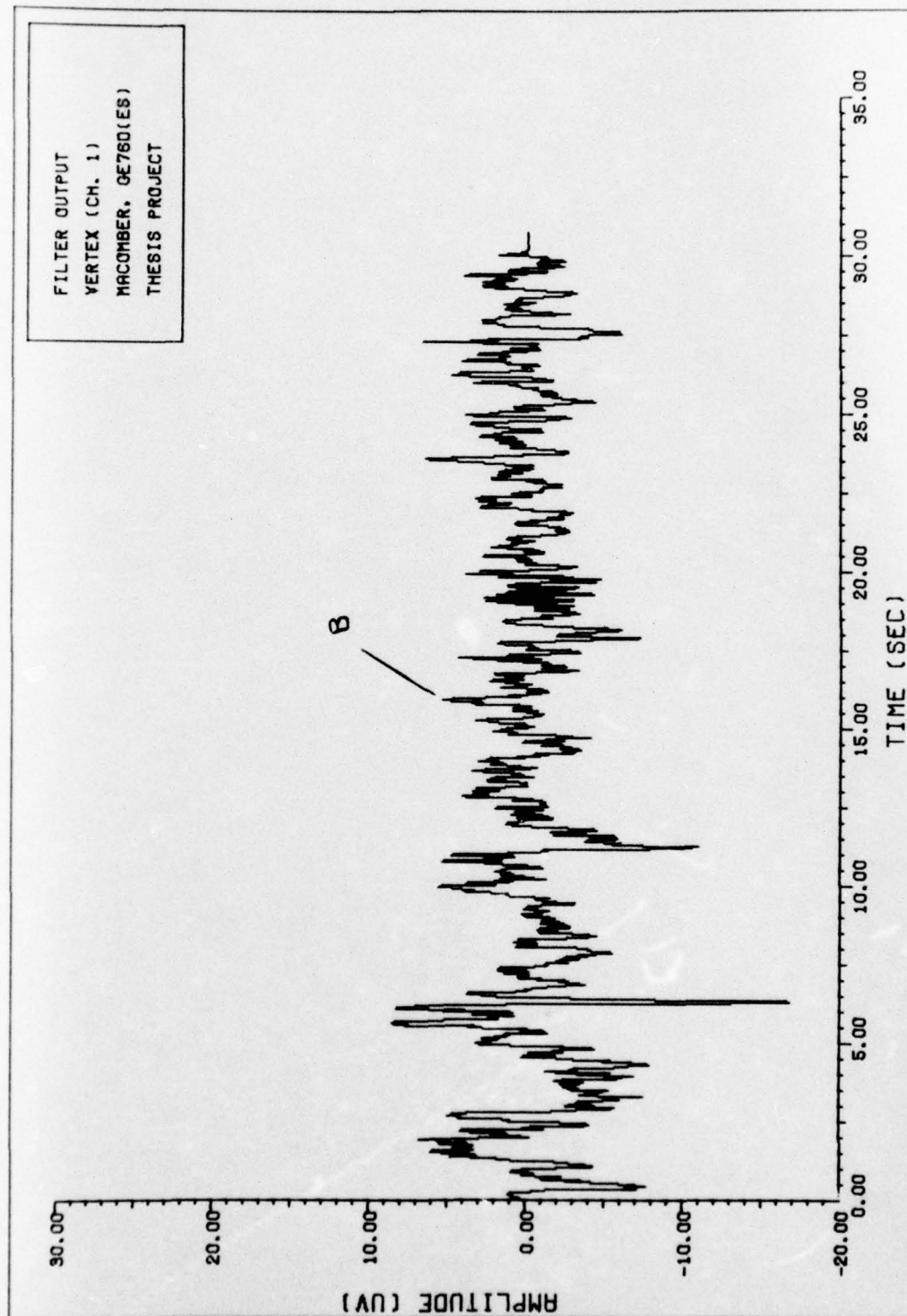
FIGURE 13A.   VERTEX FILTER OUTPUT. 1-30 SEC.
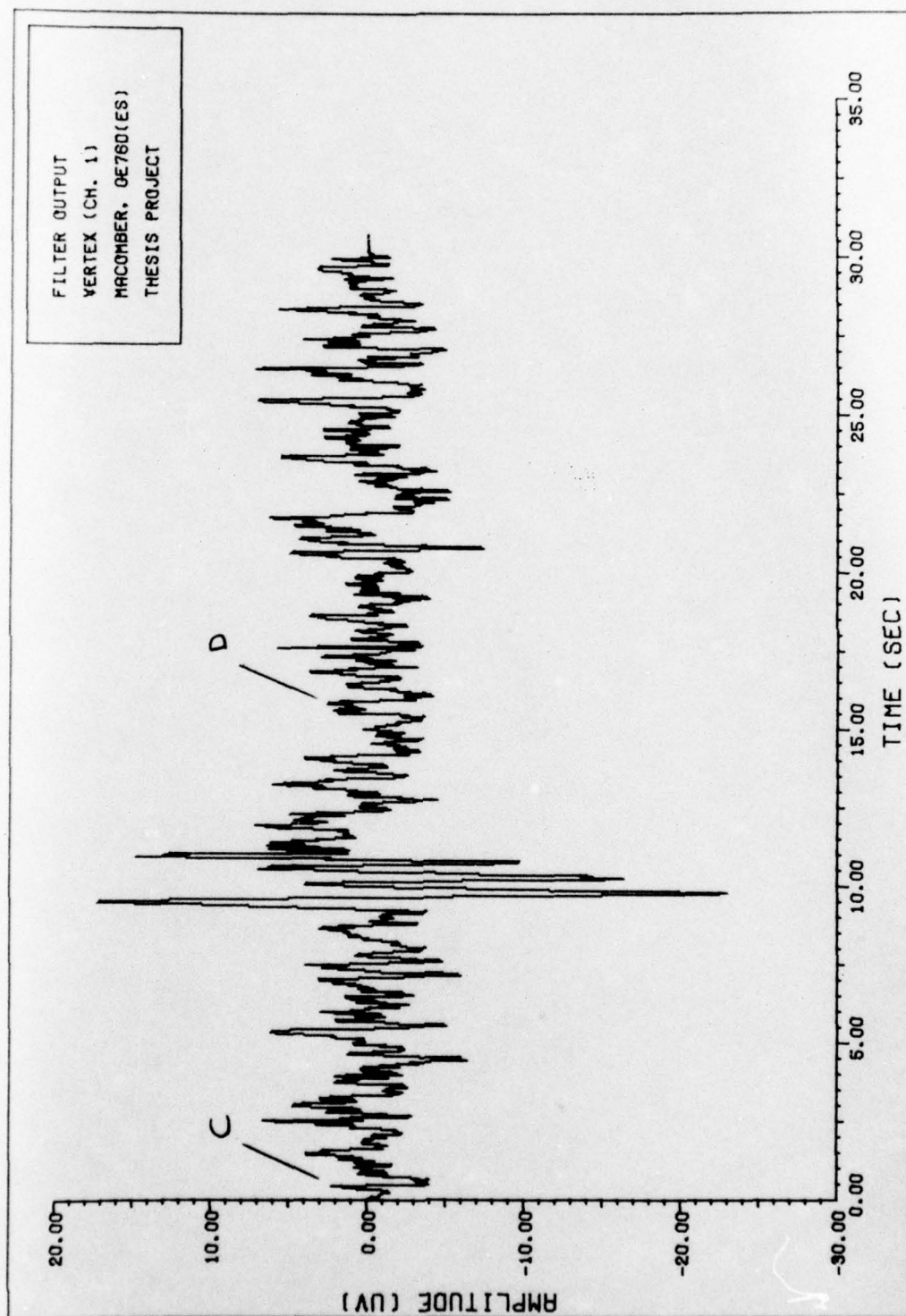
FIGURE 13B.   VERTEX FILTER OUTPUT. 31-60 SEC.

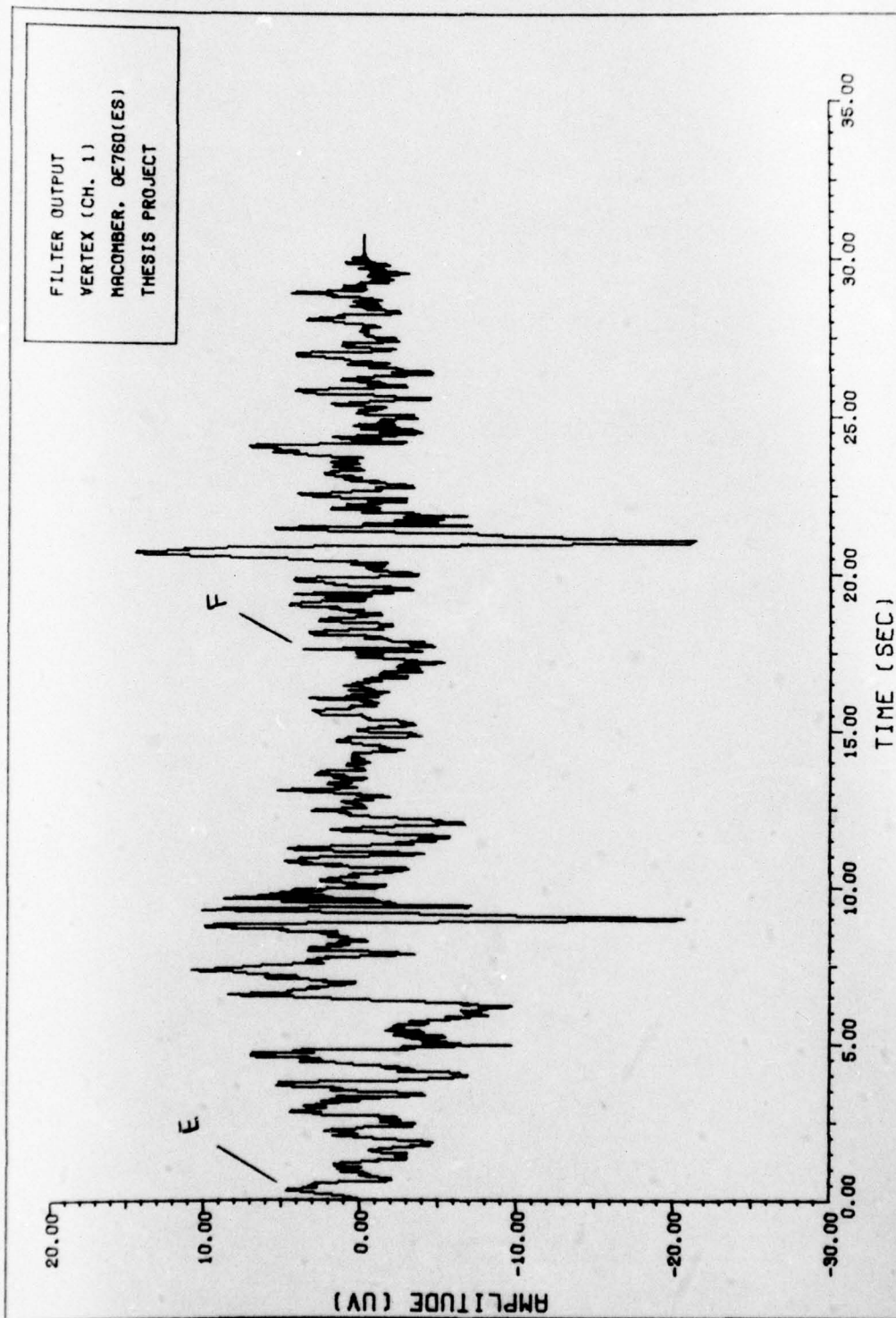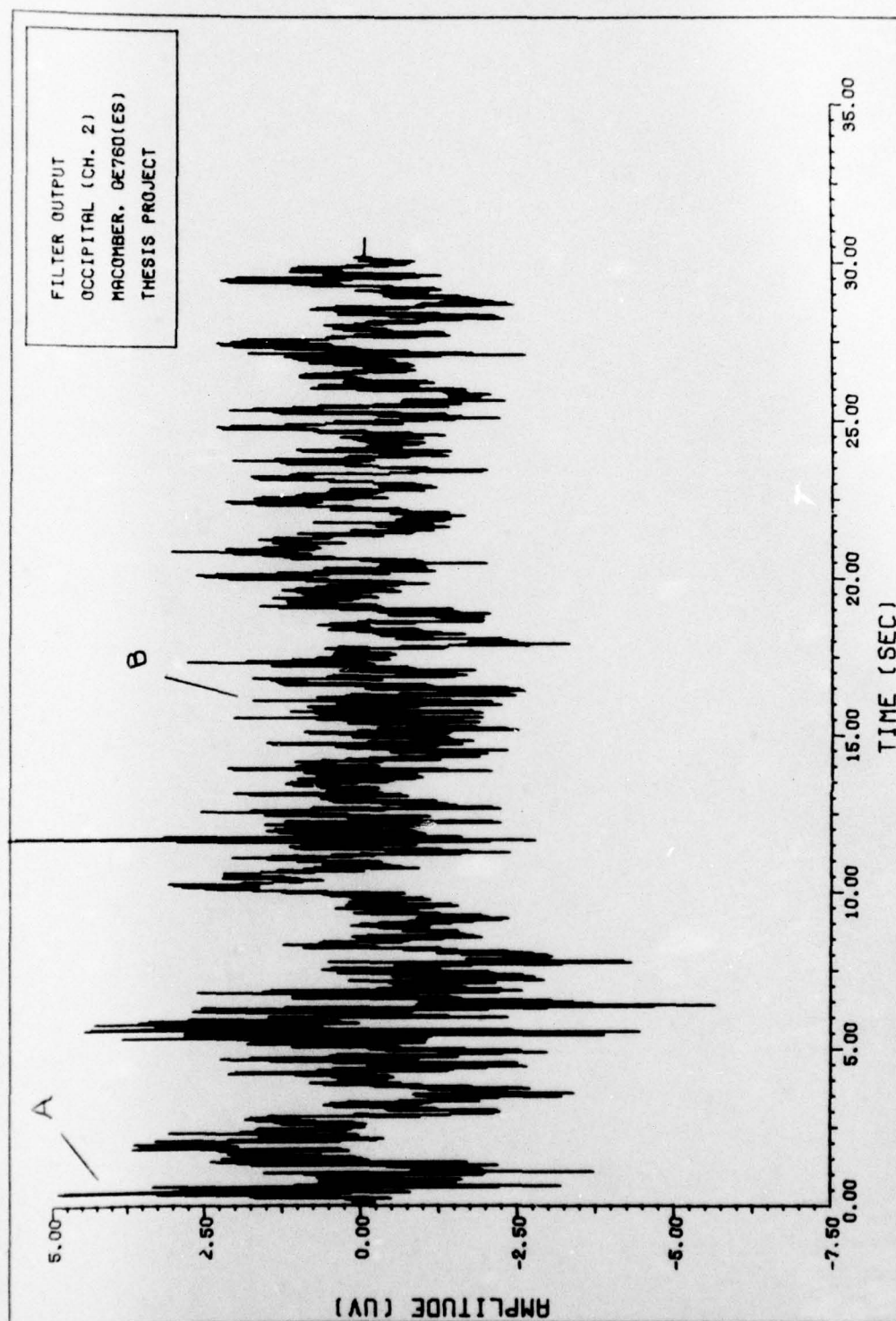FIGURE 13C.   VERTEX FILTER OUTPUT, 61-90 SEC.

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FIGURE 14A.   OCCIPITAL FILTER OUTPUT, 1-30 SEC.
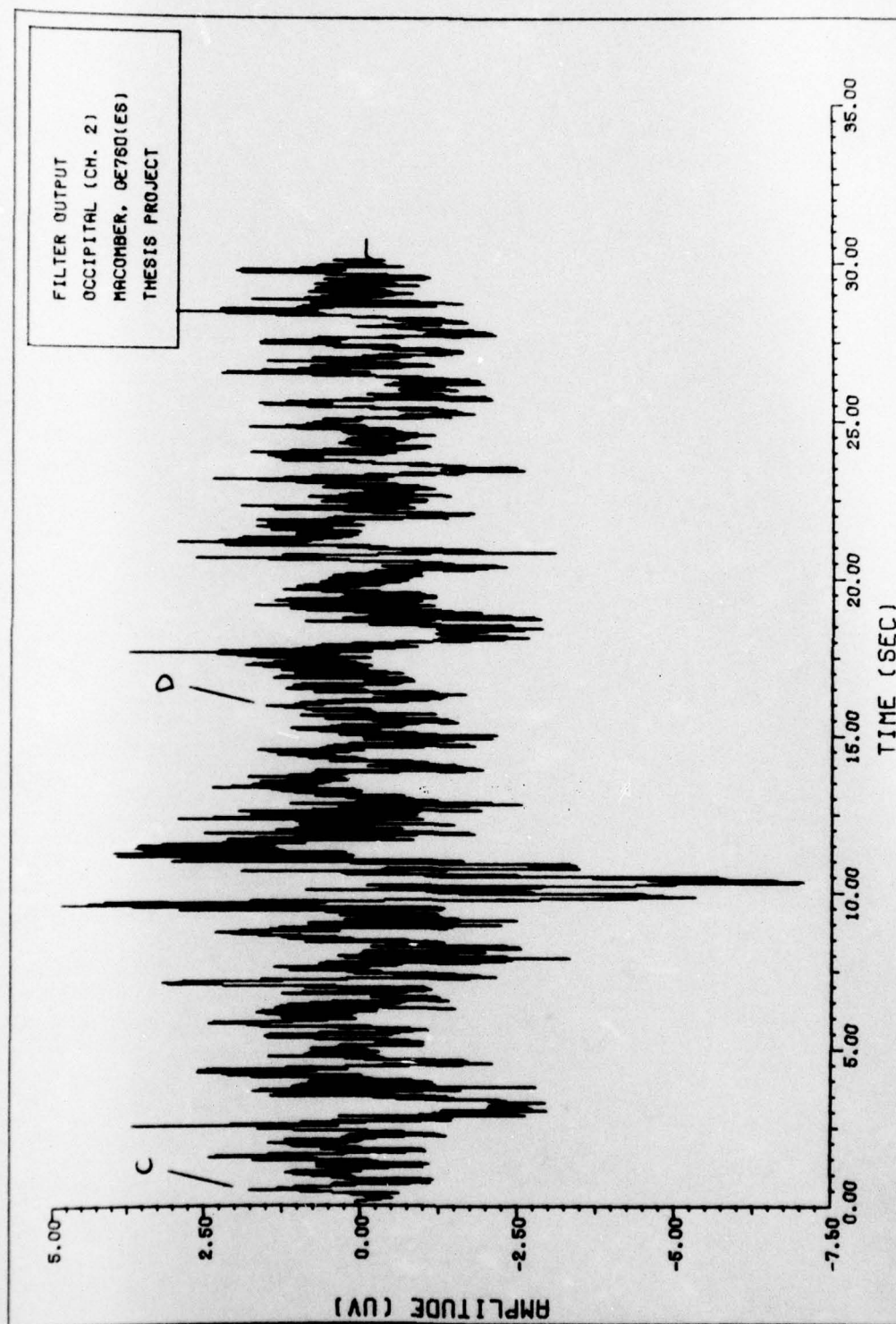
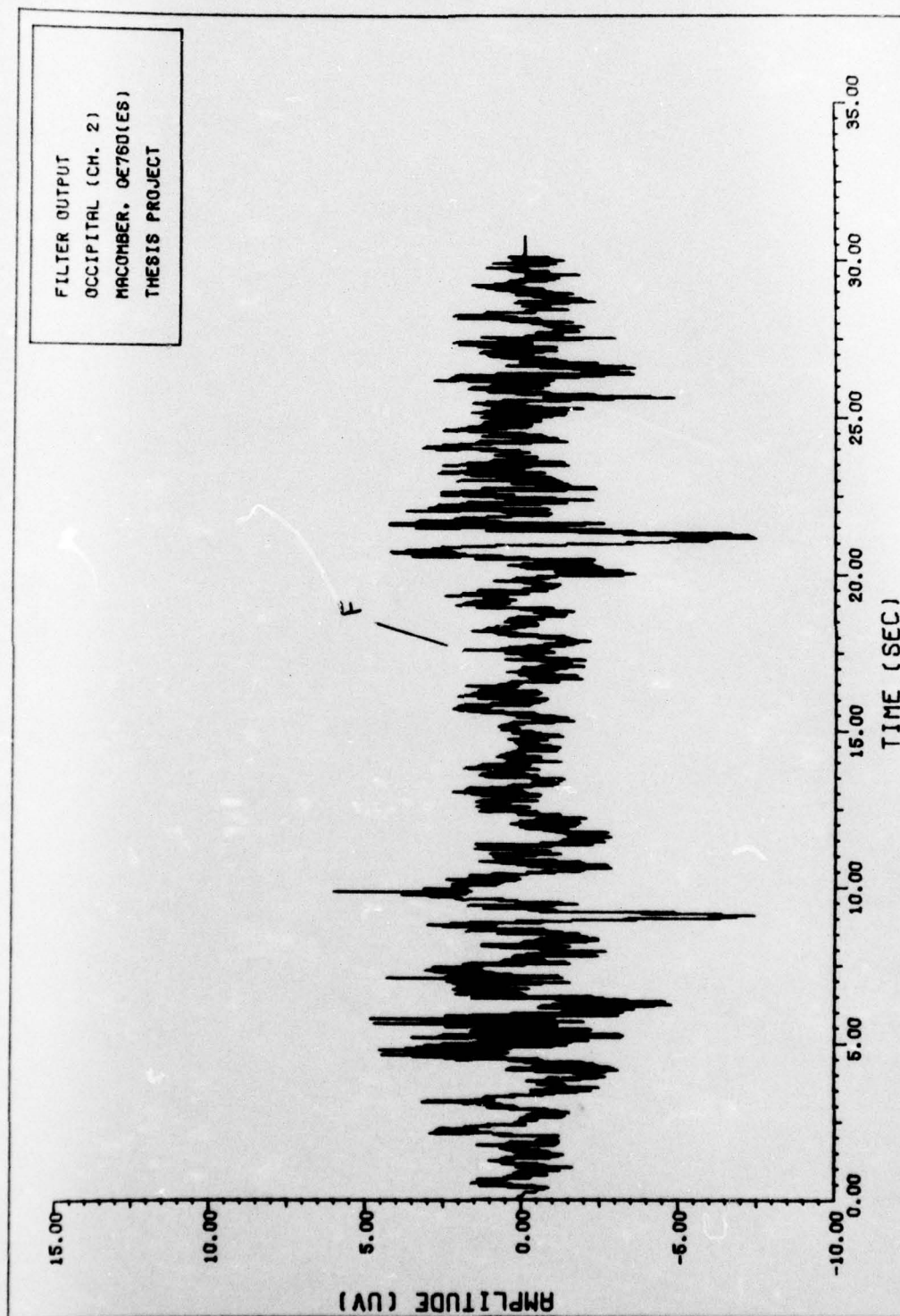FIGURE 14B.   OCCIPITAL FILTER OUTPUT. 31-60 SEC.

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FIGURE 14C.   OCCIPITAL FILTER OUTPUT. 61-90 SEC.

39 and 80 seconds as in the vertex output. However, there are other high amplitude peaks, indicating a good match, such as the one at approximately 11 seconds for which no apparent explanation is available.

V. Conclusions and Recommendations

Conclusions

The objective of this project was to implement a detection scheme which would detect the visually evoked response to a single stimulus. This VER is known to be buried in the brain's on-going electrical activity. Based on the results of this study the following conclusions were drawn:

1. The matched filter will yield a positive detection rate of over 80 %. However, its usefulness is nullified by the high number of false alarm indications in the filter output.

2. At this point no distinction can be made as to whether the vertex data or the occipital data is more preferrable for single VER detection.

3. Because of the additional apparent matchings the matched filter by itself is not an effective method of single evoked response detection.

Recommendations

It is recommended that further study in this area consider some modifications to the basic matched filter approach described in this report. The validity of the averaged VER, which is used as the template, requires further study. There can be marked differences between any two individual responses although stability of the final averaged VER does not suggest the fluctuation of these contributing responses (Ref. 3:11-12, 2:73).

Further study is required into the relationship between the VER and the on-going background activity. The interaction between them is additive only to a first approximation. There is evidence of a non-linear or non-stationary interaction between the background activity and an evoked response. This non-linear interaction can also be inferred from an examination of evoked responses to single flashes of light such as in the present case. A large percentage of the time these individual evoked responses can be observed by the eye, despite the level of background activity - that is, the noise seems to be suppressed during the major portion of the evoked response (Ref. 3:27-28).

A final recommendation is to study the effectiveness of prefiltering the sample data with a bandpass filter to eliminate the low and high frequency noise components. Also, since alpha or alpha-like activity appears to be the major contaminant of the VER more than one bandpass filter may be in order. There is some speculation that comb filtering may provide some positive results. This technique utilizes a series of bandpass filters which pass only those frequency components that contribute to the evoked response and reject those frequency regions which are conjectured to be contaminated by noise alone (Ref. 3:113).

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Appendix A
Filter Implementation Program

```
C
C     **************************************************
C     *  THIS PROGRAM IMPLEMENTS THE TEMPLATE MATCHED FILTER TO DETECT SINGLE  *
C     *  VISUALLY EVOKED RESPONSES IN A 30 SECOND SECTION OF THE SAMPLE DATA.  *
C     **************************************************
C
      DIMENSION TEMPS(2,512),ASAMP(512),SSAMP(1024),FIL1(1024),
     1Y(30800),IBJF(1024),ID(18),X(6146)
      COMPLEX S1(1024),FF(1024),YY(1024)
C     NSAMP = SAMPLE DATA SEGMENT COUNTER
C     FIL1 = VERTEX FILTER RESPONSE
C     Y = FILTERED OUTPUT
      NSAMP=0
      READ(5,110) (FIL1(I),I=1,512)
110   FORMAT(1E11.4)
      DO 2 I=1,1024
      FIL1(I)=0.
2     CONTINUE
      DO 3 I=1,30720
      Y(I)=0.
3     CONTINUE
      READ 160,(ID(I),ID(I+1),I=1,17,2)
160   FORMAT(2X,A10,A10)
      READ(5,110) (FIL1(I),I=1,512)
      DO 4 I=1,1024
      FF(I)=CMP_X(FIL1(I),0.0)
4     CONTINUE
      CALL FFT(FF,10,-1)
C     FF = DISCRETE FOURIER TRANSFORM OF THE FILTER RESPONSE
5     READ(7)I1,I2,(TEMPS(1,I),I=1,500)
C     TEMPS = TEMPLATE DATA (NOT USED IN THIS PROGRAM)
```

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```
      IF(EOF(7)) 40,5
40    READ(7)I1,I2,(ASAMP(I),BSAMP(I),I=1,256)
      READ(7)I1,I2,(ASAMP(I),BSAMP(I),I=257,512)
C     ASAMP = VERTEX SAMPLE DATA
C     BSAMP = OCCIPITAL SAMPLE DATA
      NSAMP=NSAMP+1
      IF(NSAMP.EQ.116) 42,40
42    NSAMP=0
47    READ(7)I1,I2,(ASAMP(I),BSAMP(I),I=1,256)
      READ(7)I1,I2,(ASAMP(I),BSAMP(I),I=257,512)
      NSAMP=NSAMP+1
      IF(NSAMP.EQ.59) GO TO 80
      DO 45 I=513,1024
      BSAMP(I)=0.
45    CONTINUE
      DO 50 I=1,1024
      S1(I)=CMPLX(BSAMP(I),0.0)
50    CONTINUE
      CALL FFT(S1,10,-1)
C     S1 = DISCRETE FOURIER TRANSFORM OF VERTEX DATA SEGMENT
      DO 50 I=1,1024
      YY(I)=FF(I)*S1(I)
C     YY = CONVOLUTION OF FILTER RESPONSE WITH THE DATA SEGMENT
60    CONTINUE
      CALL FFT(YY,10,1)
      LX=512*(NSAMP-1)
      DO 70 I=1,1024
      KK=I+LX
      Y(KK)=Y(KK)+(REAL(YY(I))/(1024.**2))
70    CONTINUE
```

```
          GO TO 43
C     ******************************************************************
C     *  THIS SECTION POINT SCALES THE FILTER OUTPUT AND PLOTS THE RESULT.  *
C     ******************************************************************

90        J=1
          XX=0.
          X(1)=0
          DX=0.001
          DO 150 I=2,30720
          XX=XX+DX
          IF(ABS(X(J)-XX)*.2+ABS(Y(J)-Y(I))*.05.LT.0.01) GO TO 150
          J=J+1
          X(J)=XX
          Y(J)=Y(I)
150       CONTINUE
          CALL PLOTS(IBUF,1024,44PLOT)
          CALL PLOT(0.,-4.,-3)   $   CALL PLOT(0.,.03,-3)
          CALL HGRAPH(X,Y,IJ,1,0,74)
          CALL PLOTE(1)
          END
```

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<u>Vita</u>

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER GE/EE/77-1	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Implementation of a Method to Detect the Single Visual Evoked Response		5. TYPE OF REPORT & PERIOD COVERED MS Thesis
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Charles E. Macomber Capt USAF		8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS Air Force Institute Of Technology (AFIT/EN) Wright-Patterson AFB, Ohio 45433		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Aerospace Medical Research Laboratory (AMRL/HEA) Wright-Patterson AFB, Ohio 45433		12. REPORT DATE January 1977
		13. NUMBER OF PAGES 55
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for Public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES   Approved for public release; IAW AFR 190-17

Jerral F. Guess, Captain, USAF
Director of Information

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Evoked Response
Signal Processing
Power Spectrum
Matched Filter
Discrete Fourier Transform

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The visually evoked response (VER) is one neural response to an external event. Through computer averaging techniques the evoked response to a particular stimulus is readily available. However, there are some anticipated applications which require detection of the VER after a single stimulus presentation.

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

This report describes an attempt to detect the single visual evoked response. The approach taken is based on the similarity of the problem to that of radar detection in which a known signal is buried in noise. Using the discrete Fourier transform (DFT) and other digital signal processing techniques a filter matched to the VER template was computed and implemented on a digital computer.

Computation of the matched filter required an estimate of the noise power spectrum, where the noise in this case is the on-going electrical activity of the brain. This was accomplished by averaging modified periodograms. Data from both the vertex and occipital regions were filtered to determine if one region produced better results than the other.

The results indicate that the matched filter will detect the single evoked response. However, the false alarm rate is high. The filtered output for data from both regions indicate there were several stimuli in a given time period when few were actually presented. These results give rise to the conclusion that some components of the on-going activity match well with the filter. It is suggested that the effectiveness of the matched filter approach may be improved by prefiltering the sample data to remove the contaminating components.